TECHMIND RESEARCH
ISSN: 2292-1648

International Journal of Management Excellence
Volume 2 No. 1 October 2013

Market Risk Quantifications: Historical Simulation Approach on the Malaysian Stock Exchange

Zatul Karamah Ahmad Baharul Ulum[1]

[1]Senior Lecturer, School of Business and Economics, Universiti Malaysia Sabah, zatul@ums.edu.my

Abstract- *This paper presents the evaluation of market risk quantifications using Value-at-Risk (VaR) approach on historical data of selected stocks traded in the first board of the Malaysian stock exchange. The data sample covers from the period ranging from year 2008 until 2012 while the holding periods and confidence levels are stated at three and two different positions respectively. Based on the historical simulation technique, mix results are shown when different holding periods are used. The study also shows the critical consideration when selecting the observation periods length and confidence levels in determining the VaR values.*

General Terms- *Simulation; Market Risk.*

Keywords- *Value-at-Risk; Historical Simulation*

1. INTRODUCTION

Market risk means any exposure to undesirable market movements. Bessis (1998) declares that market risk consists of adverse deviation of the mark-to-market value of the trading portfolio. According to Fallon (1996) compared to other risk, the market risk seems to be the central risk faced by most financial institutions. The essential part of market risks that financial intermediaries need to handle includes price, interest rate, currency exchange rate risks, volatility, correlation and inter-relations (Gastineau, 1993). JP Morgan (1996) reports that the measurement and management of market risk have progressed rapidly since the 1980s. The idea of managing market risk must be emphasized by market participants, since it aids the welfare of all the firm's stakeholders. In fact the objectives of managing market risk are vast, according to Duffie and Pan (1997). However, those important ones as highlighted by these authors are intended to measure the degree of risk exposure, to quantify and allocate each cost of capital to the market value and risk In early 1990s, Value-at-Risk (VaR) has gain an immense popularity and becomes an integral risk management tool and a standard to monitor and control firm's risk exposures. Jorion (1996) defined VaR as an approach that summarizes the worst expected loss that an institution can suffer over a target horizon under normal market conditions at a given confidence level.

Thus, the main objective of this study is to determine the VaR using the historical data using selected main board stocks traded in the Malaysia stock exchange. The approach is to apply the historical simulation which is part of VaR full valuation approach.

The flow of the paper covers section 2 which provides the review of literature. Section 3 highlights the description of the research data. The explanation on the methodological part in section 4 focuses on the historical simulation approach. Following the results in section 5, the summary of the study's findings and comments in section 6 concludes the paper.

2. LITERATURE REVIEW

Historical simulation (HS) is an approach which estimates VaR from the distribution of profit or loss simulated using historical returns data. In other words, it relies on a uniform distribution to sample any innovations from the past (Dowd, 1998). HS acts as the most simplistic approach of the full-valuation category (Manfredo & Leuthold, 1998). HS, also known as bootstrap simulation (Barone-Adesi & Giannopoulos 2001), allows calculation to consider nonlinearities and non-normal distributions. It also captures gamma, vega risk and correlations within historical data. Further benefits include not relying on any specific assumptions about valuation models or stochastic market structure, taking into account "fat-tails" and not being prone to model risk (Jorion, 2006).

Under this approach, selected financial instruments are analyzed over a number of days in the chosen historical observation period (for example 100 days). The actual change in each financial instrument's value is then calculated using a desired time horizon for instance 1-day. To finalize the computation, the distribution is analyzed statistically. In the case of 100 observations, the fifth lowest observation value would be the 1-day 95% confidence interval VaR. Without making any arbitrary distributional assumptions, as reported by Barone-Adesi and Giannopoulos (2001), HS can be a practical approach, particularly when there is an abnormally large historical loss. One exceptional property of HS is its underlying assumption that the past and present moments of the risk factors return density function are constant and equal. Besides that says De Brouwer (2001), HS does not require at all any underlying model to explain the market price stochastic behaviour.

Earlier studies which highlighted HS were carried out by Hendricks (1996) and Mahoney (1996). Hendricks (1996) compared twelve VaR models which consisted of five EQMA models, three EWMA models and four historical simulation models. Applying them to eight major currencies, the study failed to justify any model which captured risk most efficiently. However, the author claims that the choice of confidence level and the length of the observation period may increase the reliance on historical simulation as a better solution. All the VaR models in this study measured the intended risk particularly at the confidence interval of 95%. The research also provided evidence that longer holding period record more accurate VaR results, as well as evidence that EWMA models are able to cover time-varying properties of the portfolio return.

Like Hendricks (1996), Mahoney (1996) reported that chi-square goodness-of-fit tests clearly validated the dominance of historical simulation over variance-covariance. This was resolved using slightly different data, consisting of a 1,000 rolling sample selected randomly from both foreign exchange and global equity indexes under various confidence levels and sample periods. The study showed that VaR models performed slightly better at the 95% confidence level compared to the 99% level. The writer also illustrated that the equity portfolio give more biased VaR estimates compared to the foreign exchange data. This output quantified the notion that VaR sensitivity also depends on the types of data being analyzed.

A similar conclusion was reached by Jackson, Maude and Perraudin (1997) which showed HS is more suitable for data that exhibit fat-tails. Nonetheless, the research data were slightly different compared to those of Hendricks (1996) and Mahoney (1996) in that the information being analyzed was the bank's actual capital with relation to VaR. Longer observation horizons also were identified as a better time period because they manage extreme conditions more efficiently.

Collectively, HS as reported by Mahoney (1996) is much more flexible, easier to implement and simpler to be understood by market participants. Linsmeier and Pearson (1996) add that HS does not rely on any distributional assumptions and is independent of model risks generated by parameter estimation. Furthermore, it is also free from computation of a covariance matrix or correlation effects between assets in a portfolio because its underlying concept is based on profit and loss distribution. Hence, any erroneous estimation from these correlation parameters can be avoided. In addition, Vlaar (2000) confirms that the accuracy of VaR estimates increases as the sample of data covers a longer horizon. However, the issue on resolving how long the data must be set for a reliable value of VaR remains uncertain. Hendricks (1996) for example finds that five years data is proper while Basle Committee recommends using data covering the past three to five years should the historical simulation be used in the analysis.

3. DATA

The dataset is comprised of 20 selected stocks traded in the main board of the Malaysian stock market. The returns of the selected stocks are then divided into several groups based on the trading horizon and holding period. This covers a one year period starting from January 2, 2012 until December 29, 2012 and five years period from January 2, 2005 until December 29, 2012. The frequencies for the data base are set at one day, ten days and one month holding period. Table 1 briefly describes the models for the chosen portfolio. The net investment of the equally weighted portfolio is RM1 million.

Table 1: The Portfolio

Model	Data Base	Holding Period
1	5-year trading days	1-day
2	1-year trading days	1-day
3	5-year trading days	10-days
4	1-year trading days	10-days
5	5-year trading days	1-month
6	1-year trading days	1-month

4. METHODOLOGY

As mentioned by Beder (1995), the main parameters to determine the VaR values are the selection of the holding period and the confidence level. The choice of these components will greatly affects the nature of the VaR model. For this study the one-day, ten-day and one-month period are chosen alternately. Different holding periods are chosen because it represents the speed of the portfolio turnover (Jorion, 1997).

An important assumption underlying the historical simulation technique is that the historically observed factor changes used in the simulation are taken from independent and identical distributions (iid). Referring to Dowd (1998), suppose the study has *t* observations starting from period 0 to t, the portfolio return R_t^p over period t is

$$R_t^p = \sum_{i=1}^{N} w_i R_{i,t}, \quad t = 0,\ldots,T$$

where

$R_{i,t}$ = return to asset i over period t

w_i = relative weight of asset I in the portfolio

N = total assets in the portfolio

Here, each t observation reflects a particular portfolio return R_t^p. The sample of the historical observation returns will then give a sample of hypothetical portfolio returns distribution. Next is to translate from portfolio returns to portfolio profits and losses. This is done by arranging the resulting series of historical returns in ascending numerical order (for example from -0.01%, 1%, 2% etc.). The changes are then determined from desired percentile of the histogram of profits and losses. For instance, a sample of 1000 daily observation based on 95% confidence level, the fifth percentile is given by the fiftieth smallest change in the portfolio. Finally, the percentage value corresponds to the specific point in the historical series is multiply by the portfolio net monetary value of investment.

5. RESULTS

The one year period is chosen because it helps to portray any short-term movements in the portfolio risk while the five years observation tends to increase the probability of measuring the historical percentile more accurately. Figure 1 (a) and (b) illustrate the one-day historical returns both for model 1 and 2.

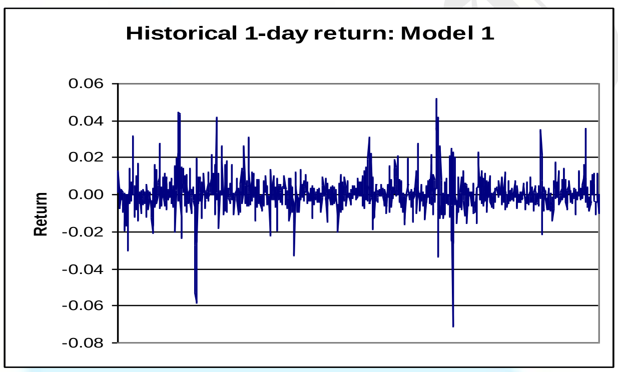

Figure 1 (a)

In average there are 1304 observations for the first model and 261 observations for the second model which covers five trading years. For the ten-days holding period, Figure 2 (a) and (b) show 130 and 26 observations for periods covering five and one year respectively. Figure 3 (a) covers 61 observations of five years data and Figure 3 (b), 13 observations for the one year data. Figure 4 displays the VaR calculations for all the VaR models. Each value denotes that the probability of the portfolio to incur any loss is either equal or greater than the shown statistics is five percent (represents by VaR 95%) or one percent (represents by VaR 99%). For instance, based on the assumptions made to operate the historical simulation over the five year period, the probability is five percent that a loss is more than or equal to 0.40 percent of the RM1 million portfolio investment will occur over a one-month holding period.

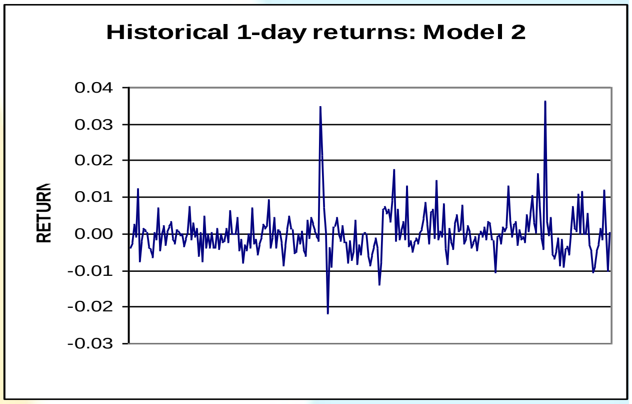

Figure 1 (b)

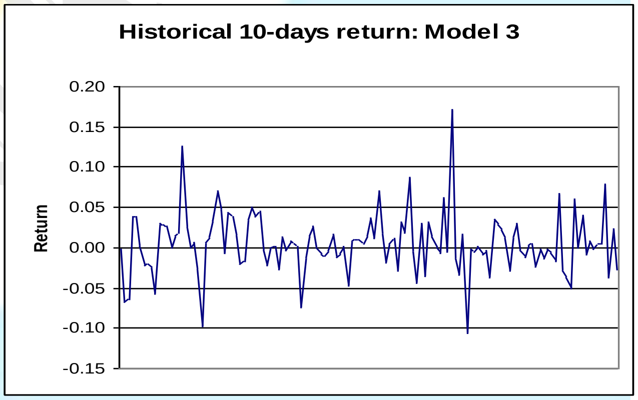

Figure 2 (a)

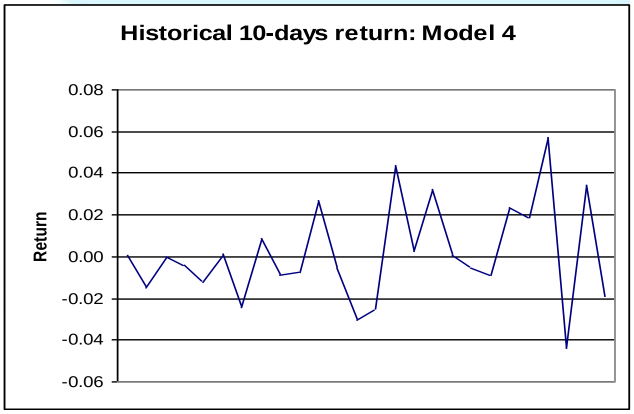

Figure 2 (b)

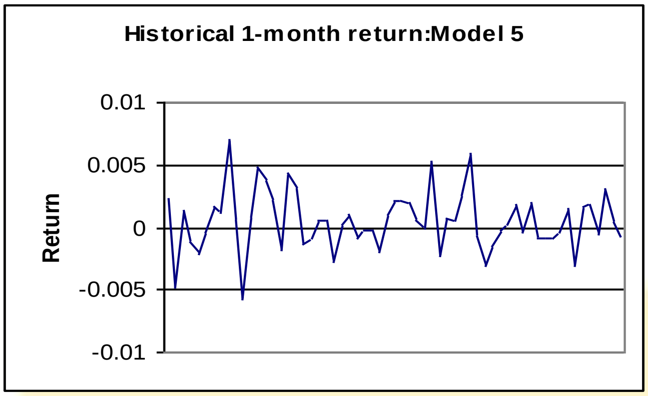

Figure 3 (a)

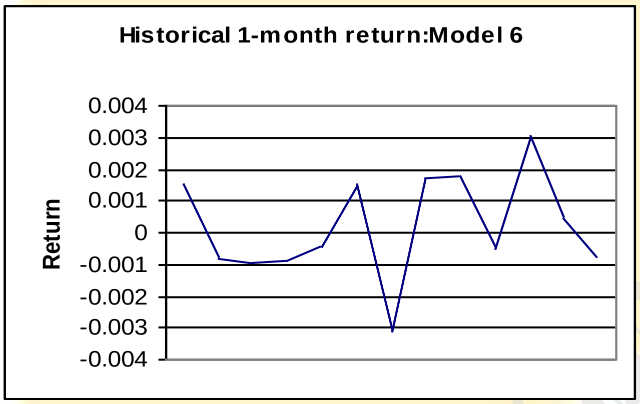

Figure 3 (b)

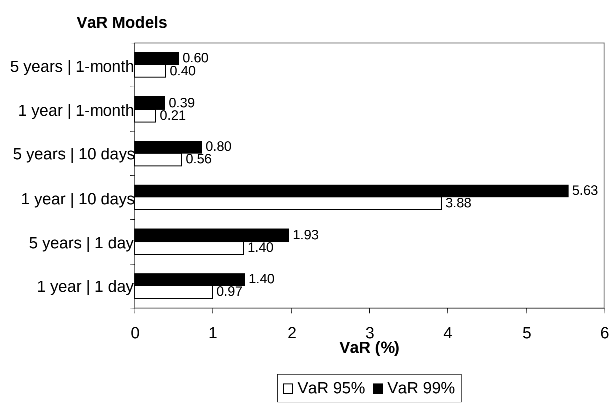

Figure 4

And by considering the net investment of RM1 million, for all models, the worst estimated loss for the portfolio at 99% depicts higher volume than at 95%. The highest amount of expected loss in this study is reflected by the portfolio traded for one year ten-days holding period giving a total of RM39,191.85 for VaR at 95% and consecutively RM55,429.77 at 99%. Table 2 summarizes the results for the models.

6. DISCUSSIONS

One-day holding period: Consistent with its underlying theory, as shown in the first two models, the VaR result increases with the time horizon. Compare to one year, the five years observation shows higher VaR values at both the confidence levels of 95% and 99% (denote 1.40% and 1.93% in contrast with 0.97% and 1.4%). This is because with longer observation, the returns of the portfolio tend to be more volatile thus increases the VaR estimates. Higher risk also associates with longer observation. This is in line with the standard deviation (SD) values calculated for both models (0.009 and 0.005 respectively). Thus, lengthening the data sample tends to produce larger VaR numbers. Similar conclusions are consistent with earlier studies by Beder (1995) and Hendricks (1996) in that the length of the observation period is one of the important elements in estimating VaR.

Ten-days holding period: In contrast with the one-day holding period effects, the one year observation shows an abrupt shift in the statistic values of VaR both at the 95% and 99% confidence level (3.88% and 5.63% respectively). This indicates contrasting results with Beder (1995). An argument on these outcomes can be attributed to the fact that for the ten-days holding period, the selected stocks in the portfolio may capture less rapid turnover. In addition according to Dowd (1998) the turnover may relate to the direct relationship with the probability of the portfolio returns to grasp market information efficiently. The distinct result between model 1 and 3 can be explained by the pattern of returns during the specific periods [Figure 1(a) and 2(a)]. Negative returns are more common over the five years one-day time horizon than over the five years ten-days time horizon. Thus, VaR value is higher for the one-day (model 1) compare to the ten-days horizon (model 3).

One-month holding period: For this setting, similar to the one-day holding period effects, the fifth and sixth models also presents increment in the VaR values as the length of data increases. Cited by Hendricks (1996), the application of simulation on longer data clearly reflects two major financial market data features. First, the market movement is not constant over time (this reflects the conditional volatility circumstances) and secondly, more extreme outcomes can be captured in the distribution. Less total observations in both one-month holding period models attribute to smaller VaR values (0.39 and 0.60 respectively) than the previous four models.

Confidence level: As illustrated in Figure 4, the historical examinations of the portfolio show that chosen confidence levels influence the VaR values. As each model's level of confidence is increased across the six models, the VaR values differ slightly (except in the case of one year ten-days). Similarly, the results of this study are consistent with those found in Beder (1995). Note that, although the historical simulation enables VaR to be inferred at any level of confidence, Dowd (1998) emphasizes that careful attention should be given when selecting higher confidence level in this procedure. Unless the sample size is particularly large, historical simulation may generate unreliable estimates.

Table 2: VaR Summary

Model	**1**	**2**	**3**	**4**	**5**	**6**
	5 years | 1 day	**1 year | 1 day**	**5 years | 10 days**	**1 year | 10 days**	**5 years | 1month**	**1 year | 1month**
Mean	0.000516	0.000116	0.000498	0.001325	0.000500	0.000198
Standard Deviation (SD)	0.009681	0.005170	0.003673	0.027891	0.002550	0.001634
VaR calculation at 95%	1.40%	0.97%	0.56%	3.88%	0.40%	0.21%
Historical VaR per million at 95%	RM14,000	RM9,714	RM5,602	RM38,819	RM40,000	RM2,191
VaR calculation at 99%	1.93%	1.40%	0.80%	5.63%	0.60%	0.39%
Historical VaR per million at 99%	RM19,300	RM14,079	RM8,365	RM56,310	RM5,910	RM3,915

7. CONCLUSIONS

Concisely, this study shows that the length of the observation period and the level of confidence are important in quantifying the market risk based on the VaR values for stocks traded in the Malaysian stock market. Results illustrate that the estimated maximum loss or in other words the value of an investment that is at risk will increase as the observation periods and confidence levels are higher. However, when apply to different holding periods the effects on the VaR estimates are rather mixed. Somehow in this case (with selected stocks), VaR fails to be the sole risk measure because of its inability to show firm's true risk exposures.

The reason for this can be attributable to the fact that the historical simulation is highly dependent on historical data which assume past event reflects future risks. Furthermore, the procedure only quantifies risks as reflected in an estimated historical period (Dowd, 1999). As indicated by Hendricks (1996) when the historical data covers too long a period it may not reflect the market situation in more recent times thus reducing the accuracy of the VaR. Thus the VaR estimate can also be less sensitive to new information. On the contrary, Kupiec (1995) emphasizes that a relatively long comparison sample period should be accommodated in order to increase the reliability of performance-based verification approach (including VaR). Shorter period time period may however create estimation error (Jorion, 1997).

In conclusion, the application of historical simulation in determining the market risk based on VaR should be used with caution. As a result, Beder (1995), Jorion (1997) and Dowd (1999) strongly suggested that VaR should be accompanied with stress testing. By evaluating each confidence level accuracy and VaR models efficiency, it is possible to enhance the capabilities of VaR as a market risk measurement standard. Consequently, this will definitely assist to minimize the expected losses depending on the length of time when one engages in stock market investments.

REFERENCES

[1] Barone-Adesi, G., & Giannopoulos, K. (2001). Non-parametric VaR techniques, myths and realities. Economic Notes by Banca Monte dei Paschi di Siena SpA, 30(2-2001), 67-181.

[2] Beder, T. 1995. VaR: Seductive but dangerous. Financial Analyst Journal. 51 (September/October):12-24

[3] Bessis, J. (1998). Risk Management in Banking. New York: John Wiley & Sons, Ltd.

[4] De Brouwer, P. (2001). Understanding and calculating Value at Risk. Derivatives Use, Trading & Regulation, 6(4), 306-322.

[5] Dowd, K. 1998. Beyond Value at Risk. England: John Wiley & Sons.

[6] Dowd, K. 1999. A value at risk approach to risk-return analysis. Journal of Portfolio Management. 25(4):60-67.

[7] Duffie, D. & Pan, J. (1997). An overview of value at risk. Journal of Derivatives. 4(Spring): 7-49.

[8] Fallon, W. (1996). Calculating VaR. The Wharton School. Retrieved August 2, 2006, from http://www.gloriamundi.org

[9] Gastineau, G. L. (1993). The essentials of financial risk management. Financial Analysts Journal, 49(5), 17-21.

[10] Hendricks, D. 1996. Evaluation of value-at-risk models using historical data. Federal Reserve bank of New York. Economic Policy Review. 2(April):39-70.

[11] Jackson, P., Maude, D., & Perraudin, W. (1997). Bank capital and value-at-risk. Bank of England Quarterly Bulletin(May), 177-184.

[12] Jorion, P. 1996. Risk2: Measuring the risk in VAR. Financial Analyst Journal. Nov/Dec 52 (6):47-56.

[13] Jorion, P. 1997. Value at Risk: The New Benchmark for Controlling Market Risk. Chicago: Irwin.

[14] Jorion, P. (2006). Value at Risk: The New Benchmark for Controlling Market Risk. (Third ed.) Chicago: Irwin.

[15] JP Morgan. 1996. RiskMetric Technical Document. New York.

[16] Kupiec, P. 1995. Techniques for verifying the accuracy of risk management models. Journal of Derivatives. 3:73-84.

[17] Linsmeier, T.J. & Pearson, N.D. 2000. Value at Risk. Financial Analyst Journal. P47-67.

[18] Mahoney, J.M. 1996. Empirical-based versus model-based approaches to value at risk: An examination of foreign exchange and global equity portfolios. Proceedings of Joint Central Bank Research Conference. Board of Governors of the Federal Reserve System. 199-217.

[19] Manfredo, M. R., & Leuthold, R. M. (1998). Agricultural applications of value-at-risk: A perspective. OFOR Paper number 98-04.

[20] Vlaar, P.J.G. 2000. Value at risk models for Dutch bond portfolios. Journal of Banking and Finance. 24(7):1131-1154

Author's Biography

Zatul Karamah A.B.U. PhD, is currently a Senior Lecturer at the School of Business and Economics, Universiti Malaysia Sabah. Her research interest includes Financial Risk Management, Insurance and Corporate Governance.